THE PENNSYLVANIA STATE UNIVERSITY
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DEPARTMENT OF FINANCE

# AN ANALYSIS OF U.S. MERGER ARBITRAGE SPREADS

GRACE FOPPIANI HILL
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Reviewed and approved* by the following:

David Haushalter
Associate Professor of Finance
Thesis Supervisor

Brian Davis
Clinical Associate Professor of Finance
Honors Adviser

* Signatures are on file in the Schreyer Honors College.

## ABSTRACT

Changing market conditions such as market volatility, liquidity, transaction costs, and the popularity of the investment strategy itself, drives merger and arbitrage deal spread fluctuations. This paper examines a sample of 349 merger and acquisition deals from years 2000-2015 in order to identify the variables, particularly those related to liquidity, to answer the question: why do merger arbitrage spreads vary throughout time?

In order to address this question, a time-series analysis of the gross spreads of completed M&A activity between the years 2000-2015 in the United States is conducted. A discussion of the mechanics of merger, or risk, arbitrage strategies, and historical types of merger analysis outlines the spectrum of methods for studying merger arbitrage spread variation. This leads into the topic of gross spread compressions, which is the specific focus of the quantitative analysis. The methodology is subsequently presented, along with the explanatory variables chosen to test against the dependent variable, gross spread. These explanatory variables focus on liquidity conditions within the United States during this time period, and singular and multivariate regressions are run to test for statistically significant relationships. A brief description of the results from the study follows. Finally, an analysis of the results, implications, and shortcomings of the study will conclude the paper.

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## ACKNOWLEDGEMENTS



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# Chapter 1: Introduction

Arbitrage activities have long been heralded as a method of maintaining the efficiency of markets. Arbitrageurs make a theoretically riskless profit by the simultaneous buying and selling of an asset where there is a price discrepancy across markets. Therefore, they benefit from the difference in the lower purchase price and higher selling price. Arbitrage activities help to keep market prices close to the fair value of a given asset. Arbitrage activity is also credited for preventing financial valuation bubbles, provides market liquidity, and reduces transaction costs (Melka and Shabi, 2013, 40). In risk arbitrage strategies specifically, where arbitrageurs take advantage of the difference in the bidding and market prices in merger and acquisition (M&A) deals.

## Risk Arbitrage Strategy Fundamentals

First, the basic progression of an M&A deal is investigated. Once a merger has been announced with a corresponding bid, the target's stock price is expected to move closer to the bid in the coming days, to reflect the bidding firm's valuation. At this point, many holders of the stock prefer to sell the target's shares. Arbitrageurs in cash mergers can take those sold shares and wait until the merger has been completed. In order to hedge against market risk, the arbitrageur will short the stock of the acquirer simultaneously (Mitchell and Pulvino, 2012, 487).

There are three primary types of transactions in M&A arbitrage strategies: cash deals, stock deals, or combined cash-stock deals. The choice of what medium of payment is used heavily affects the arbitrageur investment process (Melka and Shabi, 2013, 33). In cash deals, it is common for the bidding target to offer a higher cash payment than what the company's current

market share price is (33). For cash deals, the arbitrageur strategy is simple. They simply buy shares of the target company at announcement, hold the shares until the deal closes, and profit from the closing spread (37). Without incorporating tax effects, the gross return for an arbitrageur upon the finalization of the deal can be expressed as: *Gross return = (Offer price / Share purchase price) - 1* (35).

In stock deals, or share swap offers, the bidding firm acquires the target company's shares using its own shares as payment. Arbitrageurs profit from these deals by buying target shares long, and short selling the acquiring shares. Therefore, if and when the deal finalizes, the target shares will be exchanged for acquirer shares, which can then be used to pay back the borrowed shares. Compared to all cash deals, share swap offers are more complex and costly, as there can be costs associated with the borrowing of shares from a prime brokerage. When the deal closes, the target shares are converted into shares of the acquiring firm, which can then be used to repay borrowed shares. The acquiring firms shares serve as the currency of payment, so the success of this strategy depends on the buoyancy of the acquiring firms share prices (Melka and Shabi, 2013, 39).

Finally, cash-stock deals combine stock and cash arbitrage strategies. The target firm's shares are valued on a cash-per-share basis, with the bidding firm also offering some amount of their own shares (Melka and Shabi, 2013, 46). Arbitrageurs will once again long the target stock and short the acquirer stock simultaneously. Some deals will also give shareholders the option to choose the method of payment at the deal's closing (49).

Arbitrageurs are interested in the timetable of the deal, as it provides information to calculate the annualized returns to compare transactions. Annualized returns can be calculated through simpler interest or compound interest formulas. The preference between the two commonly corresponds to the perceived duration of the deal. Simple interest will be used for deals with shorter duration (<1 year) (Melka and Shabi, 2013, 35).

Although arbitrage strategies are theoretically riskless, risk arbitrageurs depend on the successful completion of a deal. Whether the deal closes can affect the returns of risk arbitrage strategies. If the deal is successfully finalized, the return will equal the spread ex ante. If the deal fails, losses can occur, but are more difficult to predict than profits. The categories that make up the risk of failure are: the inability of the bidding firm to secure financing, anti-trust laws that prevent mergers that damage a sector's overall competition, target shareholder disapproval, administrative authorization, MAC clauses, reverse termination fees, fraud, and due diligence (Melka and Shabi, 2013, 60-65). When a deal breaks, two forces drive the target stock price back downward. One force is whether the failure is due to some defect within the target company itself. The other downward force is the mass exit of all arbitrageurs. Other outcomes could include a counteroffer or a renegotiation in the offer at a reduced price (38). The sample used for the regression analysis of this paper only includes deals that have successfully been completed in an effort to minimize the affects of firm-specific risks on the aggregate gross spread during this period.

# Chapter 2: Historical Merger Activity in the U.S

Chapter 2 reviews the logic that drives businesses and other market actors to enter the M&A market, and what factors impact their performance. Before specifically addressing gross spread compressions or liquidity in relation to the gross spreads of M&A deals, the following sections give background for how merger activity has previously been studied. The foundational theories of merger activity apply different perspectives, and the implications of these disparities in thought.

## Theories of Merger Activity

Despite the general agreement that the 1960's and 1980's are two periods in US history that saw large waves of M&A activity, a debate exists on what the underlying market forces are responsible for merger activity. Two different schools of thought divide merger theory: neoclassical and behavioral. Neoclassical theory of mergers holds that mergers are a reactive method of increasing efficiency in the market when an industry experiences a destabilizing factor or shock (Shleifer and Vishny 2003, 296). Behavioral theories use the underlying motivations of market actors to assess how these behaviors can aggregate and drive merger activity.

### Neoclassical Theories:

Gort (1969) and Mitchell and Mulherin (1996) posit that merger waves are rationally driven by economic, regulatory and technological shocks, which trigger widespread asset reallocation

(Harford, 2005, 530). Through the study of industry-level merger waves throughout the 80's and 90's, Harford (2005) expands upon these neoclassical conclusions by suggesting that merger waves are a result of industry shocks, accompanied by capital liquidity to facilitate these movements (Harford, 2005, 530). Harford rejects the notion that behavioral misvaluation factors drive waves, and instead sees heightened merger activity as a consequence of economic expansion and capital liquidity. He reasons that once companies have an economic motivation to make a transaction, low transaction costs will further incentivize merger activity (Harford, 2005, 530). This paper's research question is modeled off of this assumption that capital liquidity affects levels of merger activity.

***Tobin's Q Theory of Investment:***

Tobin's Q ratio has served many purposes in studies examining merger and acquisition spreads and returns through the neoclassical lens, commonly compared between bidding and target firms. The Q-theory of investment holds that as a firm's Q (or the ratio of market value to replacement cost of capital) rises, investment rate should rise correspondingly (Javonic and Rousseau, 2002, 198). Servaes (1991) repurposed the Q-theory of investment by building upon the work of Lang, Stulz and Walkling (1989) to relate increased M&A activity to managerial performance (Servaes, 1991, 418).

Javonic and Rousseau (2002) also relate clustered merger activity to high dispersion in q ratios and technological changes. The authors introduced the Q-Theory of Mergers as an extension of the Q-theory of investment, however, they hold that M&A investments of companies have a

greater sensitivity to company Q-ratios than direct investment activities (Jovanovic and Rousseau, 2002, 198). Their findings coincide with previously held neoclassical explanations for heightened merger activity. Also, from Jovanovic and Rousseau (2002) comes the argument that the merger waves in the 1920's, 80's, and 90's were due to reallocation forces catalyzed by technological market destabilization. The authors recognize, however, that this reallocation explanation is not applicable to the merger wave seen in the 1960's, which they refer to as the 'hubris' wave (Jovanovic and Rousseau, 2002, 203).

Rhodes-Kropf et al. (2005) provide a regression-based analysis on the firm- and sector-wide misvaluation levels, as well as long-run growth opportunities for M&A market actors. In their paper titled, “Valuation waves and merger activity: The empirical evidence”, the authors use two approaches to circumvent the use of neoclassical concepts to explain their results. The first approach is derived from the work of Jovanovic and Rousseau (2002)**,** using Tobin's Q as the ratio to measure deviations in company market and book values, used as a proxy to relate economic shocks and reorganization opportunities (Rhodes-Kropf et al., 2005, 595). When comparing the Q ratio of failed and successful mergers, however, the results indicate that the failed deals have lower levels of misvaluation in the long run (Rhodes-Kropf et al. 2005, 595). This partially contradicts the logic of Lang, Stulz and Walkling (1989), Servaes (1991), and Javonic and Rousseau (2002) who support the notion that completed mergers represent the reassignment of target assets in order to make room for business opportunity and growth (Dong et al, 2006, 727).

***Rational RKV Decomposition Theory:***

Rhodes-Kropf and Viswanathan (2005) analyze valuation error in merger activity through a rational lens. The theory posits that “correlated misinformation" is a driver of misvaluation in merger waves (Rhodes-Kropf et al. 2005, 562). This theory also stresses the difference between firm-specific and sector- or market-wide misvaluation (563). Market- or sector-wide overvaluation applies to a target firm's estimations of market synergies. When the market is overvalued, target and bidding companies' error in estimations of market synergies will increase (565). Although the source of misvaluation may not be known to either, this theory assumes that the private information of both the target and bidding firms will indicate internally whether they are under- or overvalued (Rhodes-Kropf et al. 2005, 565). This holds with neoclassical theories, as overvaluation in the market, paired with the assumption that managers are making optimal decisions, is what drives merger waves.

The authors conclude that cash targets and acquirers are undervalued relative to stock targets and acquirers, respectively. Short-run firm- and sector-wide misvaluation is positively correlated with merger intensity. Accordingly, the increase in merger activity should result in the convergence of the spreads (Rhodes-Kropf et al. 2005, 601). This assumption will also be incorporated into the regression analysis.

Overall, the neoclassical theories primarily focus on the ways in which M&A activity efficiently responds to market forces, including changes in capital liquidity. The rationale for the explanatory variable selection is presented through the neoclassical, efficient-market perspective.

**Behavioral Theories:**

The following section covers the broad categorizations of behavioral theories of M&A activity. The impacts of the collective attitudes and behaviors of market actors are not examined in the quantitative analysis of this paper, however they provide a critical counterargument to the neoclassical applications of merger theory.

***Theory of Stock-Driven Acquisitions:***

Shleifer and Vishny's theory of acquisitions takes an irrational position, proposing that target managers acting in their own short-term interests is what causes them to, "cash out quickly" (Rhodes-Kropf et al. 2005, 562). Shleifer and Vishny believe that neoclassical explanations of mergers focus too narrowly on industry segments, instead of aggregate market movements, do not sufficiently explain the discrepancy between time periods' measured profitability improvements, and fail to adapt predictions to the form of currency used in the deal. Shleifer and Vishny (2003) point out several ways in which the neoclassical theory of mergers is incongruous with what has been observed in the stock market in response to merger and acquisition announcements (Shleifer and Vishny 2003, 296).

For instance, in opposition to Javonic and Rousseau's (2002) "Q Theory of Mergers", Shleifer and Vishny (2003) hold that the merger wave seen the 1980's was not a response to reallocation opportunities for firms. Instead, it should be read as a response to a decade of poor stock market performance, marked by hostile takeovers and bust-ups, where the target firms were relatively

undervalued and could be purchased for cash (Shleifer and Vishny 2003, 307). This explanation is formulated with the assumption that managers are acting rationally to capture gains on the cash purchase of relatively undervalued targets, or the equity purchase of relatively overvalued targets (Dong et al, 2006, 749).

In turn, Shleifer and Vishny (2003) put forth a theory of stock-market-driven acquisitions that assumes that markets are inefficient, although market actors, such as managers, are considered rational. This theory attempts to explain: "who acquires whom, the choice of the medium of payment, the valuation consequences of mergers, and merger waves" (Shleifer and Vishny 2003, 297). Without denying the presence of mispricing, this model of acquisitions highlights how corporate policies are used as techniques to overvalue a firm's equity, allowing them to make purchases with their overvalued stock, effectively giving themselves a discount (Shleifer and Vishny 2003, 309). Analysis of the model supports Shleifer and Vishny's prediction that in stock acquisition deals, the bidder will likely be overvalued relative to the target company (Shleifer and Vishny 2003, 305).

Mortal and Schill study Shleifer and Vishny's proposition that inefficient arbitrage markets are a result of managers using overvalued stock as an acquisition currency, with investors slow to realize the overpricing (Mortal and Schill, 2015, 477). Mortal and Schill propose a different explanation. The results of their study of stock deals are inconsistent with the positions of Shleifer and Vishny. Instead of form of payment being the explanatory variable for negative abnormal returns, this study finds evidence that these abnormal returns are better explained by respective firm asset growth rates (Mortal and Schill, 2015, 478).

***Agency Model of Limited Arbitrage:***

Shleifer and Vishny (1997) analyze the effectiveness of merger arbitrage. In their agency model, Shleifer and Vishny assume that investors act upon prior beliefs of the how high an arbitrageur expected return, which determines the market share of the arbitrageurs (Shleifer and Vishny 1997, 39). Their agency model assumes that there are three market participants to recognize in the model: arbitrage fund investors, professional arbitrageurs, and noise traders. Both investors and arbitrageurs are assumed to be operating rationally, without investors knowing the arbitrageurs' trading strategies (Shleifer and Vishny 1997, 38). This reflects the secretive behavior of arbitrageurs, as their strategy must be shielded from the threat of imitation. Therefore, investors are assumed to mold their expected future returns of arbitrageurs based only on prior performance (40). If an arbitrageur is underperforming their benchmark, this will negatively affect the resources that will remain under their management (41). During periods of underperformance, three reasons are commonly identified as potential causes: "1) a random error term, 2) a deepening of noise trader sentiment (bad luck), and 3) inferior ability" (41).

Micah Officer questions the hypothesis put forth by Vishny and Shleifer (1997) concerning the effects of performance-based arbitrage. Officer examines how merger arbitrage spreads move when met with large arbitrage losses. Officer attempts to detect whether there are factors that cause spreads to widen at the same time, as a result of two liquidity event types (large losses, or "disasters", and large deal announcements). Officer finds that there is very little evidence to support this hypothesis (Officer, 2007, 811). This paper does not look at specific liquidity

events, however, it does reconsider the relationship between gross spread co-movements and measures of liquidity.

Both neoclassical and behavioral theories have been discussed in order to illustrate the wide array of factors that have relationships with changes in M&A activity levels over time. The following section will narrow the focus from M&A activity levels, generally, to M&A arbitrage spread behavior, specifically.

# Chapter 3: Compression of M&A Arbitrage Spreads

The purpose of this paper is to identify the factors that contribution to the compression of M&A arbitrage spreads, instead of M&A activity levels in general. Several published papers put forth explanations for bid-ask spread dispersion and conversion in M&A markets. For example, Jetley and Ji conducted a study observing the behavior of risk (M&A) arbitrage spreads between the years 1990 and 2007. The authors describe merger acquisition strategies as generally following the format of: longing the target's stock, preferably short after a deal's announcement, and shorting the acquirer's stock if desired. From their findings, abnormal returns from arbitrage strategies are constrained over time, meaning that the trading strategy was less profitable for participating arbitrageurs. The authors observed a decline in the spreads of merger arbitrage beginning in 1990. They attribute this decline to the increasing popularity of the trading strategy itself, which allows spreads to tighten and close (Jetley and Ji, 2010, 66).

An article published by Baker and Savasoglu (2002) examines the abnormal returns delivered by risk arbitrage portfolios, instead weighing the risks of deal completion and target company size for deals emerging in the time frame between 1981 and 1996. The authors also look at other factors that could constrain returns, such as the supply of arbitrage opportunities and other deal characteristics (Baker and Savasoglu, 2002).

The regression study presented in Chapter 5 and Chapter 6 models itself off of the two experiments described above, in that a time series of bid-ask spreads of M&A deals will be

analyzed, and relate the movement of spreads to market-wide factors conventionally referenced in neoclassical M&A theory.

# Chapter 4: Methodology

## Sample Deal Selection

A list of deals is pulled from the Thomson Reuters' Mergers and Acquisitions database. Public, US-based deals that were announced between years 2000 and 2015 are returned, operating under the assumption that non-US companies would have different risks and transaction costs. 22,728 deals are returned from the database, and an additional filter of 100% transfer of ownership is then applied to the data. This left 3816 deals in the raw data set that will eventually be used to calculate deal frequency in Chapter 6.

This list of mergers had columns for: Announcement Day, Target Company Name, Acquirer Name, Synopsis, and Price Per Share. From this data, to be referenced as the 'list of mergers', a random selection of deals serves as the sample for analysis. Individual sheets are used to list a target's stock price and dividend information from FactSet.

From here, the target company is searched in the FactSet database in order to return each target's ticker. Once the ticker is searched and placed on the header, it serves as a reference point for the daily target stock prices, also pulled from the FactSet database. The table's first column lists the deal's duration. Each company's date column starts with the announcement date and ends at the date of resolution when the ticker is no longer publicly traded. The remaining columns table are: the target stock's price at close, issued dividends, dividend-adjusted return, offer price, and gross spread in both dollar and percentage units per day. The dates, target stock prices, and issued

dividends are pulled from FactSet in reference to the target's ticker. The dividend-adjusted return is calculated using the following formula: [(Target Stock Price$_{(T+1)}$ + Target Dividend$_{(T+1)}$) - (Target Stock Price$_{(T=0)}$)] / (Target Stock Price$_{(T=0)}$). The gross spread in dollar terms is calculated by subtracting the daily target stock price from the acquirer's offer price. The relative percentage of gross value is found by dividing the Gross Spread ($) by the daily target stock price.

At this juncture, deals with offer prices less than $5.00 are filtered out of the sample. This is done to eliminate deals where even a price change of $0.10 would be magnified in the relative gross spread (%) calculations. This reduces the sample population from 450 deals to 349 deals.

**Statistical Summary of Sample Deal Data**

The remaining deal data is aggregated and summary statistics are recorded. The summary statistics, listed in Table 1, for total list of mergers data provides the target stock price ($), offer price ($), and gross spread in both dollar and percentage units for all 349 of the sample merger deals. All measures on Table 1 are taken from daily data values from individual deals, which explain the high observation count.

**Table 1: Summary Statistics for Sample List of Mergers Data** **Source: Thomson Reuters**

| | *Target Stock Price ($)* | *Offer Price ($)* | *Gross Spread ($)* | *Gross Spread (%)* |
|---|---|---|---|---|
| *Mean* | $30.77 | $31.81 | $1.05 | 4.88% |
| *Standard Error* | $0.21 | $0.21 | $0.03 | 0.10% |
| *Median* | $20.89 | $21.50 | $0.33 | 1.53% |
| *Mode* | $22.75 | $12.00 | $0.02 | 0.00% |
| *Standard Deviation* | $32.39 | $32.79 | $4.93 | 15.39% |
| *Sample Variance* | 1049.44 | 1075.28 | 24.26 | 0.02 |
| *Kurtosis* | 17.53 | 15.05 | 59.34 | 15.00 |
| *Skewness* | 3.56 | 3.31 | -0.51 | 2.58 |
| *Range* | $303.37 | $256.25 | $170.52 | 294.39% |
| *Minimum* | $1.65 | $5.00 | $(93.61) | -61.06% |
| *Maximum* | $305.02 | $261.25 | $76.91 | 233.33% |
| *Sum* | $747,827.32 | $773,269.66 | $25,442.34 | 118670.04% |
| *Count* | 24307 | 24307 | 24307 | 24307 |

**Time Series of Gross Spread**

Figure 1 plots the average gross spread of all sample deals, which will serve as the y-variable for all regression analysis. The gross spread for each merger is measured every trading day starting at the announcement date until the closing of the deal. The sharp decline in the average gross spread between years 2009 and 2010 will serve as a case to compare the explanatory variables to.

**Figure 1: Time Series of M&A Gross Spread for Completed Deals**


## Explanatory Variable Selection

All variables used in the regression analysis will be calculated on a monthly basis. Because the sample size for gross spread data rests at 349, there are days between 2000 and 2015 without any individual deal gross spread (%) calculations. By using monthly variables, all months in this time range are accounted for in the sample data. All variables are selected on the grounds of their relationship to liquidity, under the assumption that liquidity is what establishes the degree of arbitrage opportunities available in a market. This allows a platform to test the hypothesis that M&A gross spreads will widen as the degree of arbitrage opportunities fall as a consequence of lowered liquidity. This approach aligns with neoclassical theories of merger and acquisition activity, in that the market efficiency will be assumed in the selection of explanatory variables.

Each of the individual explanatory variables will be a partial expression of market liquidity conditions, in line with Harford (2005).

***Liquidity Effects on Arbitrage Opportunities***

Arbitrage upholds the law of one price, an economic theory that states that the price of any given asset should be the same across all markets (Mitchell, Pulvino, and Stafford, 2002, 551). To illustrate the effects of liquidity on the ability to arbitrage away mispricing in the market, Liu and Mello (2011)'s study on hedge fund activities during the financial crisis will be discussed. Liu and Mello (2011) found that during the financial crisis from 2007-2009, hedge funds prepared for investor redemptions by loading their balance sheets with cash. From July to August of 2008, 11% of all assets under management were cash holdings (Liu and Mello, 2011, 491). Liu and Mello (2011) question why hedge funds would not want to take advantage of the price distortions common in crises, and instead enter into a positive feedback loop of selling off positions, leading to losses and more redemptions.

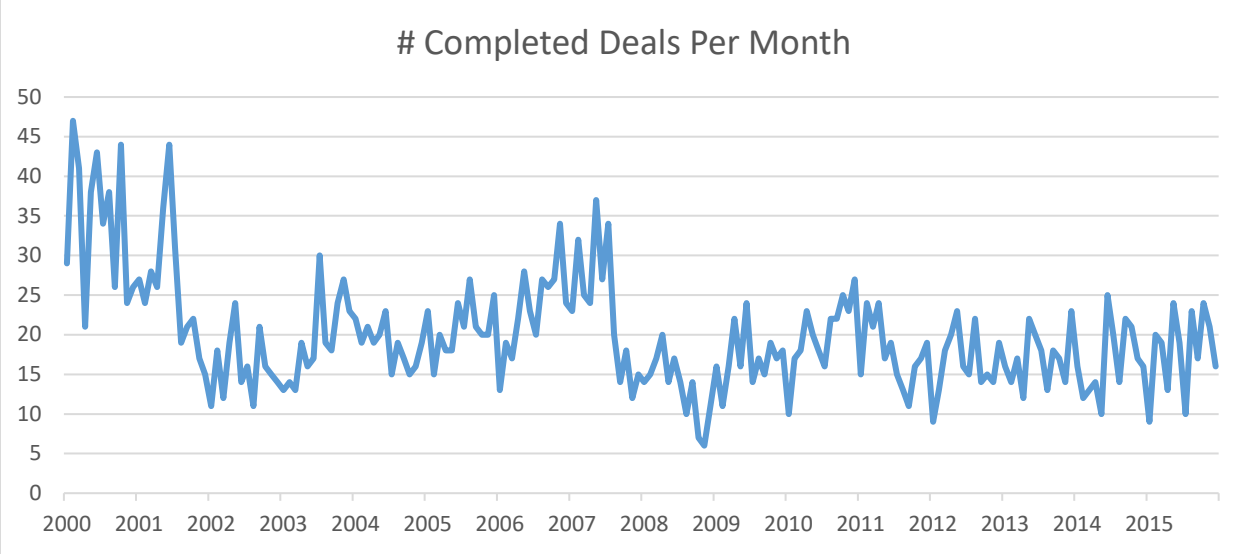
Shleifer and Vishny (1997) suggest that as investors become more sensitive to short-term losses, hedge funds respond by refraining from any investments that could return a loss in the short-term, as this may lead to further redemptions. This problem is rooted in investors' uncertainty of fundamental asset values. From their analysis, the authors conclude that the limits to arbitrage are market illiquidity and coordination problems (Liu and Mello, 2011, 492). In the United States, the liquidity run in 2008 will provide evidence for the explanatory variables' reactions to reduced liquidity.

**Defense of Explanatory Variable Selections**

***Deal Frequency (# of deals announced per month)***

In the wake of the financial crisis, trading activity slowed dramatically, as wary investors refused to roll over repurchasing agreements or offer new lending (Tarullo, 2016, 10). The deal frequency will be a used as a broad measure of trading activity for M&A, in line with Harford (2005)'s neoclassical approach to understanding merger activity. Using the most basic definition of market liquidity, it is assumed that trading activity will decline with decreased liquidity (Chordia, Roll, and Subrahmanyam, 2001, 513). Deal frequency will be taken from the total list of mergers, with 3816 deals, and calculated on a per-month basis, and is expected to decrease as gross spreads increase. Figure 2 supports this theory in the persistently lower numbers seen for deal completion beginning in 2008.

**Figure 2: Times Series of Deal Frequency** **Source: Thomson Reuters**

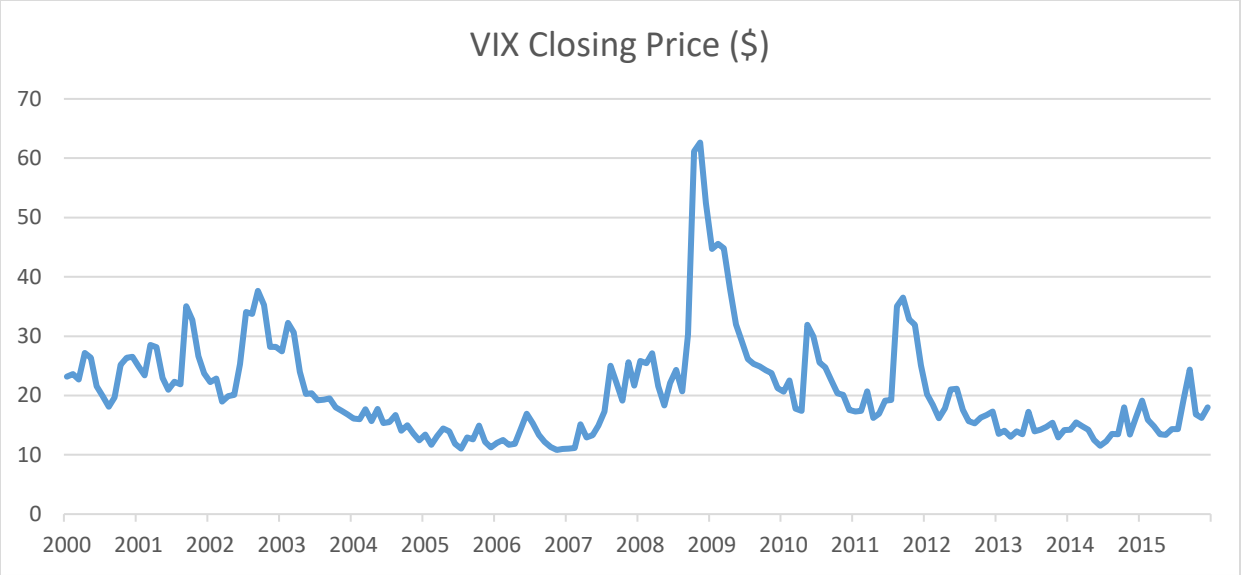


***VIX Price***

Market volatility is related to liquidity, as short-term speculative trades become riskier in highly volatile environments (Chordia et al, 2001, 513). This suggests that arbitrage opportunities will become less attractive as volatility increases, resulting in fewer participant arbitrageurs to correct widening spreads. The chosen proxy for volatility is the average closing price of the VIX per month, which measures investor expectations of volatility. The results will only refer to correlative properties of the relationship, as the VIX variable is also interpreted as heightened uncertainty, which does not hold the same relationship to liquidity as volatility.

Figure 2 illustrates the price behavior of the VIX for years 2000-2015. In the five years leading up to the 2007-2008 financial crisis, the VIX trended downward with noticeably less price movement than years prior. As volatility in the market dropped, expectations for future volatility followed. This market signal of unusually low volatility is met with the correction seen in years 2008-2009, where the price peaked in November, 2008 at $80.86. Because the units of the y-axis are in monthly terms, the highest monthly average of VIX reached $62.63. Figure 2 shows that expected volatility rose at the same time that the markets began to recognize the signs of low liquidity in 2008.

**Figure 3: Time Series of VIX Price ($)** **Source: finance.yahoo.com/quote/%5EVIX/history/**

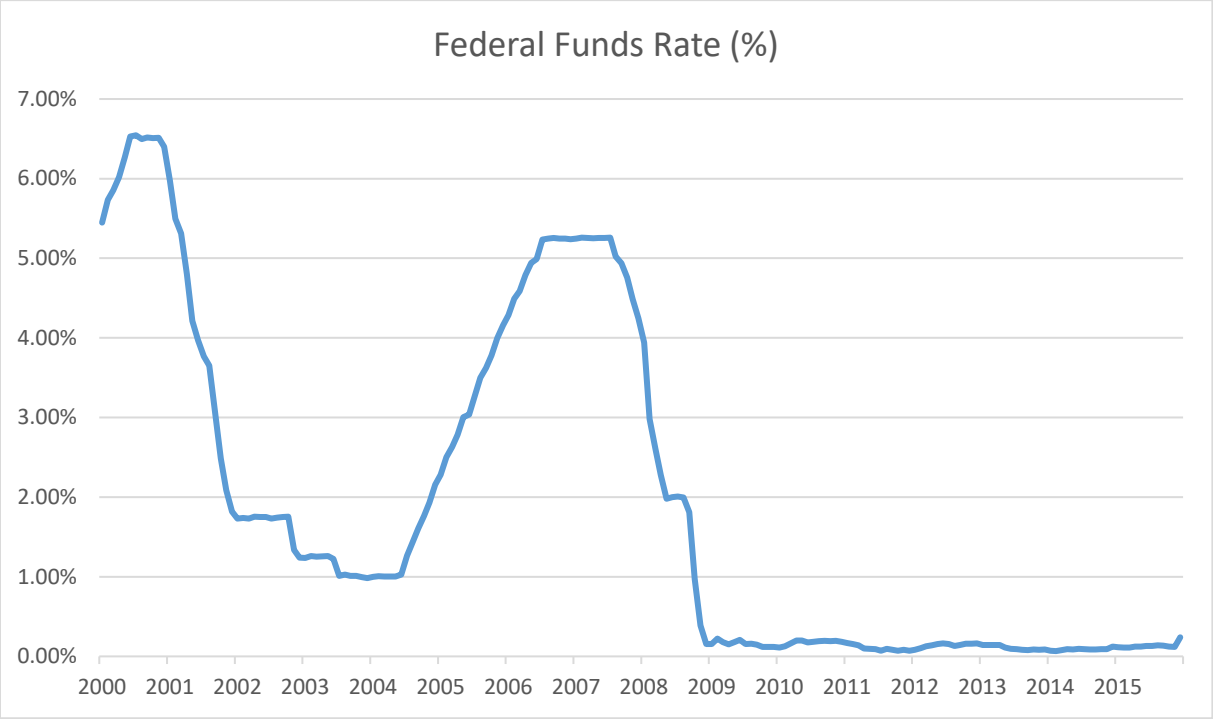



***Federal Funds Rate (%)***

Adopting the logic of Chordia et al (2001), the monthly federal funds rate can speak to the levels of market liquidity present at a given time. This is due to the fact that margin requirements and short-selling constraints are tied to the movements of short-term interest rates. Therefore, increased short-rates are assumed to constrain liquidity, as it creates market frictions, which should result in wide gross spreads as arbitrageurs are not as able to force prices back to fundamental value. This variable also captures the risk of default, where a rise in default spreads could fuel investor anxiety over holding inventory, consequentially reducing market liquidity (Chordia et al, 2001, 512). Therefore, the correlation coefficient of the Federal Funds Rate in relation to the Gross Spread is expected to be positive.

In Figure 3, there is a clear spike in the Federal Funds Rate starting in year 2004, peaking in 2007. The steep decline in the Federal Funds Rate after 2008 can be explained by the Fed's lowering of the rate in order to stimulate the economy during the liquidity run, which would have kept pushing the rate up. It is important to note that the hypothesized relationship between the gross spread and the federal funds rate may not materialize fully in the regression analysis, mostly due to the change in the Fed's approach to monetary policy. Before the financial crisis, the rate was set according the target established by the Federal Open Market Committee (FOMC). Since 2008, however, the Fed decided to purchase large quantities of long-term securities in an effort to stimulate and accommodate market actors who were interested in borrowing in the aftermath of the crisis ("Open Market Operations", 2017). This contradicts the theory that the Federal Funds Rate will increase, indiscriminately, when market liquidity decreases.

**Figure 4: Time Series of Federal Funds Rate (%)** **Source: fred.stlouisfed.org/series/FEDFUNDS**



***Change in S&P 500 P/E Ratio***

The change in the S&P 500's monthly P/E ratio will be used as a proxy measure for market-wide valuation, acting similarly to neoclassical theories of merger activity that use Tobin's Q ratio to assess market valuation trends. Widening spreads in M&A deals provide evidence for the argument that asset prices can deviate from their fundamental valuations. This debate was raised in financial economic circles when Shiller's (1981) study was published. Shiller (1981) posed the argument that asset prices from the 1970's and 1980's were too high to be entirely explained by new information hitting the price (Shiller, 1981, 434). This is an argument, which questioned the integrity of market efficiency. Now, it is understood that asset prices may deviate from their true values, especially in bull markets when investor sentiment can become a positive feedback loop. Shiller (2000) also held that the 1990's spike in prices was owed to investor over exuberance. As the P/E ratio of the S&P 500 increases, I expect that the gross spreads will increase correspondingly. This is because the ratio is to be used as an indication arbitrageurs' ability to keep valuation levels from deviating greatly. The arbitrageurs' ability to correct mispricing is partially constrained by the liquidity levels of that market. Figure 5 and Figure 6 clearly show that during there is a sharp increase and decrease in the P/E ratio, beginning mid-2008, peaking in 2009. From the theorized relationship above, this peak will be interpreted as a trend of overpricing in the market.

**Figure 5: Time Series of S&P P/E Ratio** **Source: multpl.com**

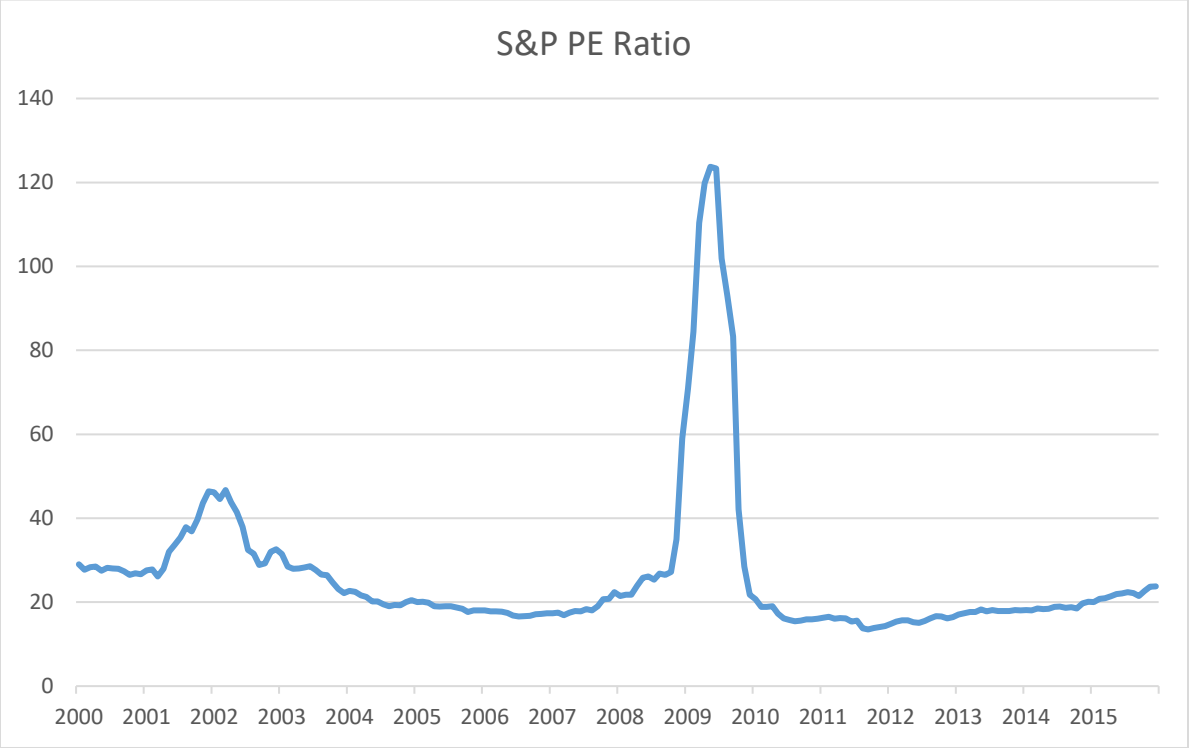
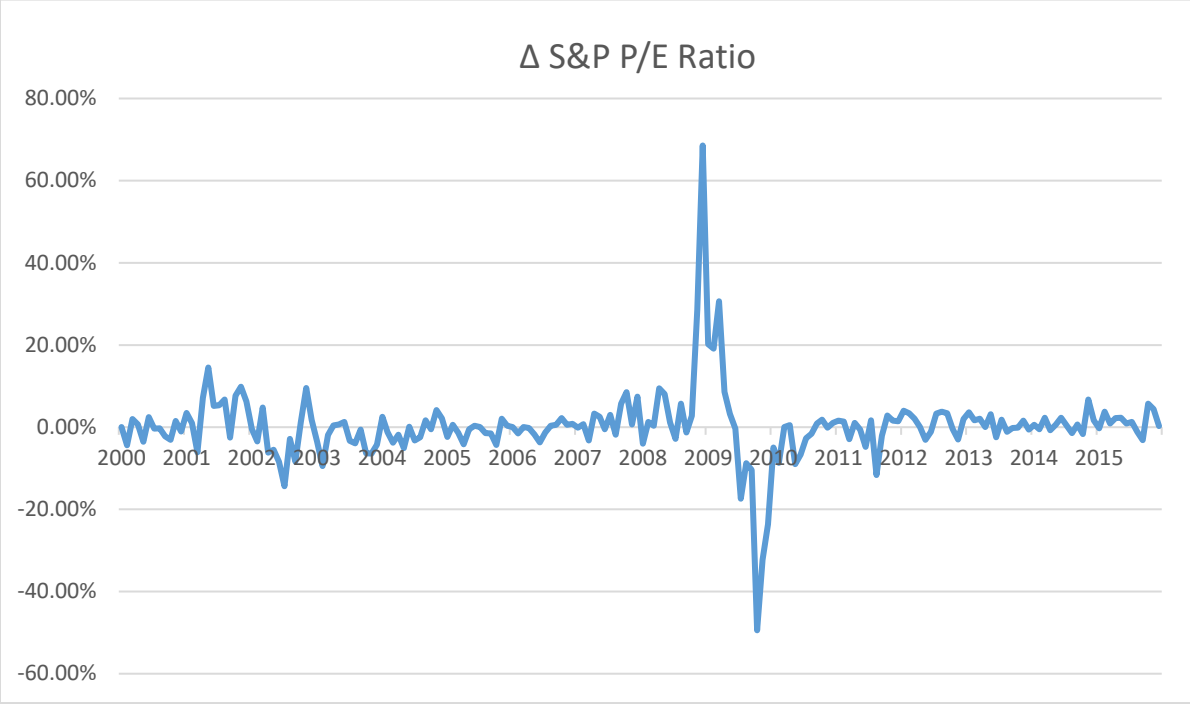



**Figure 6: Time Series Δ S&P P/E Ratio** **Source: multpl.com**



**Summary Statistics for Explanatory Variables**

Table 2 lists the summary statistics for each of the four explanatory variables. On the far right of the table, the average gross spread, or dependent variable in this experiment, is also listed for reference. All variables listed in Table 2 are expressed in monthly terms from years 2000-2015. The average deals per month

**Table 2: Summary Statistics for Explanatory Variables**

| | *Completed Deals (#)* | *VIX Price ($)* | *Federal Funds Rate (%)* | *Δ S&P 500 P/E Ratio (%)* | *Gross Spread (%)* |
|---|---|---|---|---|---|
| *Mean* | 19.83 | $20.67 | 1.87% | 0.28% | 3.75% |
| *Standard Error* | 0.51 | $0.62 | 0.15% | 0.63% | 0.49% |
| *Median* | 19 | $18.30 | 1.01% | 0.32% | 1.96% |
| *Mode* | 19 | --- | 1.01% | 0.00% | --- |
| *Standard Deviation* | 7.02 | $8.57 | 2.09% | 8.77% | 6.81% |
| *Sample Variance* | 49.22 | 73.51 | 0.00 | 0.01 | 0.00 |
| *Kurtosis* | 2.60 | 5.68 | -0.64 | 25.76 | 3.51 |
| *Skewness* | 1.33 | 1.97 | 0.89 | 1.60 | 1.27 |
| *Range* | 41.00 | $51.82 | 6.48% | 118.00% | 48.96% |
| *Minimum* | 6 | $10.82 | 0.07% | -49.44% | -17.76% |
| *Maximum* | 47 | $62.64 | 6.54% | 68.56% | 31.20% |
| *Sum* | 3787 | $3,947.52 | 358.09% | 52.88% | 717.12% |
| *Count* | 191 | 191 | 191 | 191 | 191 |

# Chapter 5: Single Variable Results and Analysis

Regressions testing the relationships between each of the individual explanatory variables and the monthly Gross Spread (%) are run. Tables 3, 4, and 5 display the statistical output for each of the regressions. In analyzing the results of the single variable regressions, I will be focusing on the R-Square, X-variable coefficient, and the P-value to gauge the statistical significance of each of the variables. As mentioned before, a negative X-variable coefficient is expected from the Deal Frequency – Gross Spread relationship, and a positive coefficient is expected from the remaining three relationships.

For the purpose of this analysis, the null hypothesis will be rejected for any P-value < 0.10. The P-value inversely signals the strength of the evidence against the null hypothesis. A higher P-value indicates that there is a greater likelihood that the X-variable coefficient is zero, or that the explanatory variable has no detectable effect on the dependent variable. Variables that return P-values < 0.10 will be excluded from the multivariate variable selection.

## Deal Frequency and Gross Spread Regression

To begin, the variable is rendered statistically insignificant due to its P-value in excess of the 0.10 threshold. Table 3 confirms that the coefficient for Deal Frequency is negative in relation to Gross Spread, and the downward slope of the can be observed in Figure 3. This corresponds with expectations about the inverse relationship of Deal Frequency and Gross Spread. Figure 1 shows that there is a greater amount of variability of gross spread in the 10-20 deal frequency range, as compared to the 30-50 range. It is not surprising that there are fewer months that had

30-50 deals per month, however, this could be the explanation for the relatively lower variability of the gross spreads from 30-50 deal frequency. An alternative explanation is that as deal frequency increases, the market will see increased trading. This would indicate is a higher level of liquidity in the market place, tightening the spread between bid and ask prices of M&A deals. The R-square value for the regression reports that only 1.17% of the data can be explained by the regression model, although there is a 13.5% calculated probability that there is no detectable relationship between the Deal Frequency and Gross Spread. This exceeds the maximum accepted P-value (<0.10) for a variable to be considered statistically significant. Overall, the monthly Deal Frequency does not have strong enough explanatory power over the Gross Spread to be used in the multivariate regression.

**Table 3: Deal Frequency vs. Gross Spread Regression Output**

| *Regression Statistics* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Multiple R | 0.108405711 | | | | | | | |
| R Square | 0.011751798 | | | | | | | |
| Adjusted R Square | 0.006522972 | | | | | | | |
| Standard Error | 0.067887745 | | | | | | | |
| Observations | 191 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.010358166 | 0.010358166 | 2.247502054 | 0.135498752 | | | |
| Residual | 189 | 0.871052968 | 0.004608746 | | | | | |
| Total | 190 | 0.881411134 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | 0.058412692 | 0.014760638 | 3.95732833 | 0.000107175 | 0.029295929 | 0.087529454 | 0.029295929 | 0.087529454 |
| Deal Freq | -0.00105246 | 0.00070203 | -1.49916712 | 0.135498752 | -0.00243728 | 0.00033236 | -0.00243728 | 0.00033236 |

Figure 7: Deal Frequency vs. Gross Spread Line Fit Plot

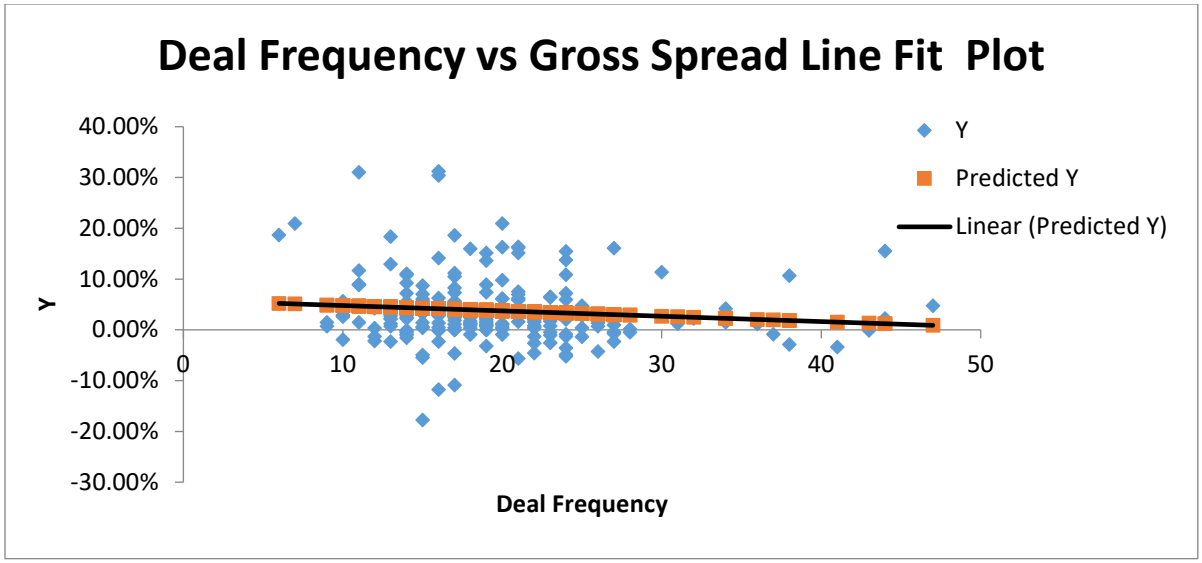
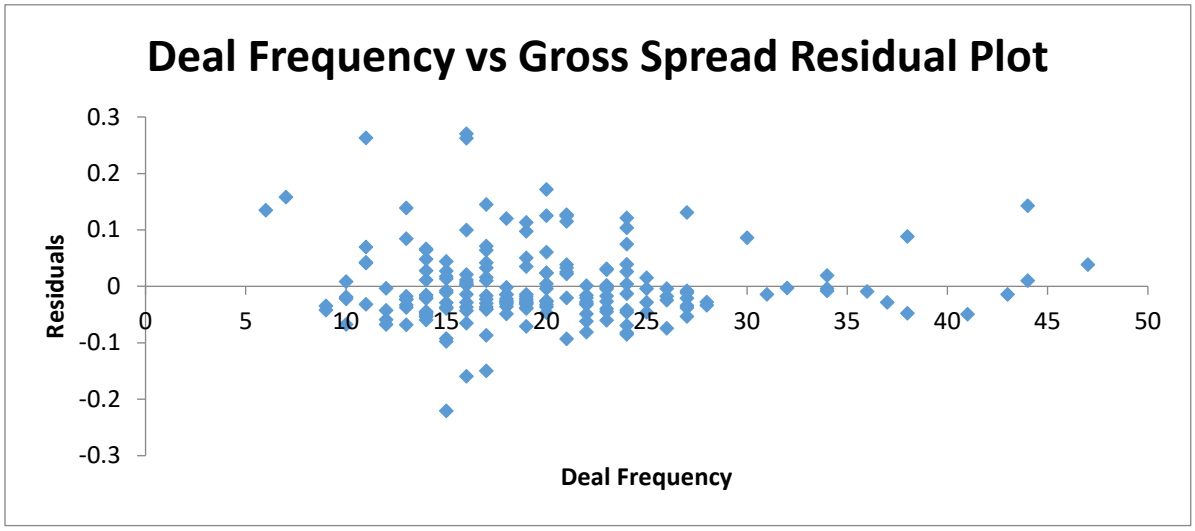



Figure 8: Deal Frequency vs. Gross Spread Residual Plot



## VIX and Gross Spread Regression

The results from the VIX vs. Gross Spread regression in Table 4 show a stronger relationship, with an R-Square value of .115. The correlation coefficient for the VIX is positive, which again confirms expectations of the directional relationship between the variables. This regression's P-value does not exceed 0.10, and therefore the null hypothesis is rejected, and retains statistical significance. Figure 3 suggests that a VIX priced at $40 or more, indicating high expectations of volatility in the future, the average of the gross spreads would have been even larger than the predicted Y values, perhaps hinting at an exponential relationship. The correlation coefficient is also trending upward among the lowest gross spreads as the VIX increases. Overall, the regression output provides substantive evidence to support the notion that as market volatility increases, the increased fluctuation of asset prices may provide the opportunity for their market prices to deviate from their fundamental values. Therefore, because a lack of liquidity is a leading factor for heightened volatility, and a lack of liquidity makes it more difficult to arbitrage mispricing away, one can reasonably expect gross spreads to increase.

**Table 4: VIX vs. Gross Spread Regression Output**

| *Regression Statistics* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Multiple R | 0.339649211 | | | | | | | |
| R Square | 0.115361586 | | | | | | | |
| Adjusted R Square | 0.11068096 | | | | | | | |
| Standard Error | 0.064230494 | | | | | | | |
| Observations | 191 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.101680987 | 0.101680987 | 24.64661206 | 1.53285E-06 | | | |
| Residual | 189 | 0.779730147 | 0.004125556 | | | | | |
| Total | 190 | 0.881411134 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | -0.018217809 | 0.012155834 | -1.498688498 | 0.135622857 | -0.042196348 | 0.00576073 | -0.042196348 | 0.00576073 |
| VIX | 0.002698089 | 0.000543473 | 4.964535432 | 1.53285E-06 | 0.001626038 | 0.003770141 | 0.001626038 | 0.003770141 |

Figure 9: VIX vs. Gross Spread Line Fit Plot

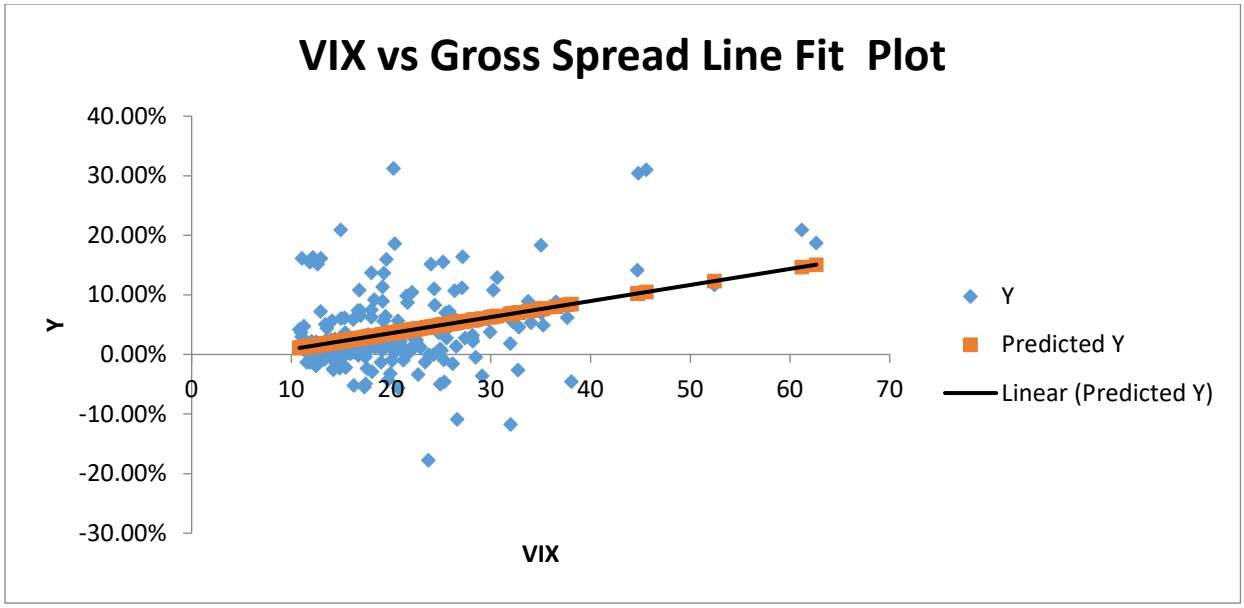
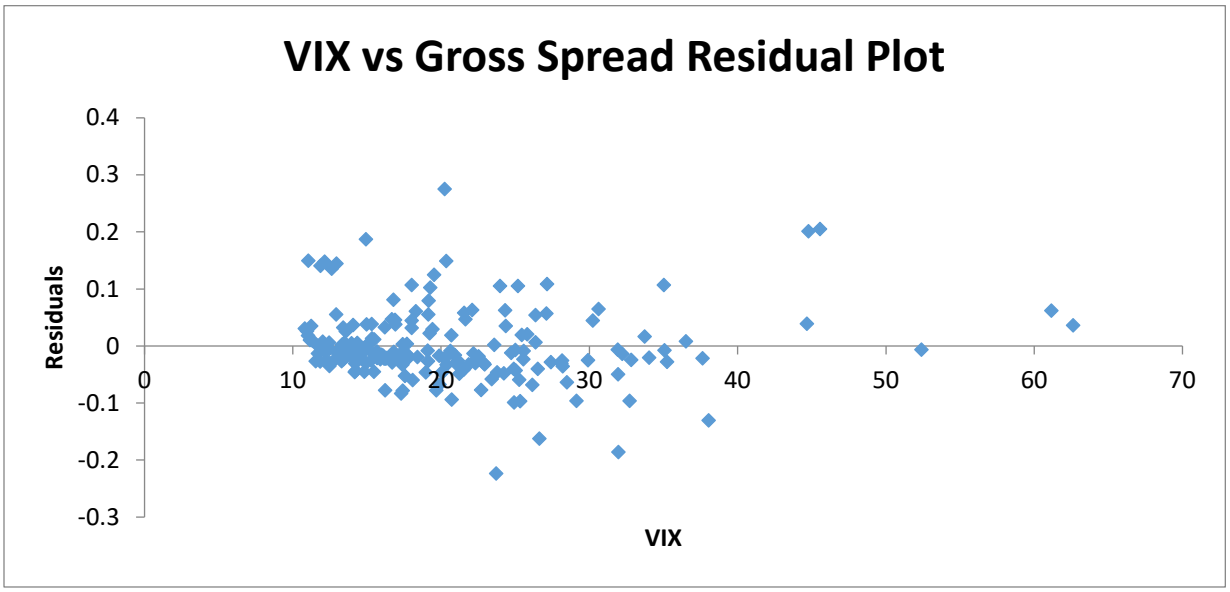



Figure 10: VIX vs. Gross Spread Residual Plot



**Federal Funds Rate and Gross Spread Regression**

The third explanatory tested is the Federal Funds Rate (average % per month). First, the positive correlation between the variables confirms expectations that as the Federal Funds Rate increases, a rise in Gross Spread will be subsequently observed. This does not speak to the power of the relationship, which is still relatively low considering the R-square value of .003. This, coupled with a P-value of .4 suggests that this variable should not be considered statistically significant in explaining the relationship between liquidity and the gross spread. Although the relationship may not be causal, it is worth noting that as the Federal Funds Rate increases, the visible variability and magnitude of Gross Spread declines. At the lowest monthly Federal Funds Rate values, particularly at just over 0%, the Gross Spread data is concentrated and has a greater range on the y-axis.

One could argue an explanation for this result rests in the fact that after a sustained increase in the rate between March of 2002 and August of 2007, the Federal Funds Rate was lowered to below 1% by the end of 2008. In October of 2008, it became clear the United States financial system was facing a liquidity crunch, which raised concerns over solvency of financial firms (Tarullo, 2016, 4). According to the logic that drove the selection of the Federal Funds Rate, rates should increase in response to the increased demand for liquidity, widening bid-ask spreads. Said another way, “liquidity is most available when you need it least and least available when you need it most" (Tarullo, 2016, 10). The Fed’s promotion of borrowing low-liquidity environments represents a synthetic or unnatural change in the rate in order to encourage

borrowing at the beginning of the liquidity run in the United States. Therefore, the high P-value and low R-square may be partially explained by the fact that other forces capable of degrading the theoretical association affected the Federal Funds Rate and Gross Spread relationship.

**Table 5: Federal Funds Rate vs. Gross Spread Regression Output**

| *Regression Statistics* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Multiple R | 0.06087614 | | | | | | | |
| R Square | 0.0037059 | | | | | | | |
| Adjusted R Square | -0.0015655 | | | | | | | |
| Standard Error | 0.06816354 | | | | | | | |
| Observations | 191 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.003266425 | 0.003266425 | 0.7030212 | 0.40282954 | | | |
| Residual | 189 | 0.878144709 | 0.004646268 | | | | | |
| Total | 190 | 0.881411134 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | 0.03382235 | 0.006636398 | 5.096493055 | 8.3553E-07 | 0.020731429 | 0.04691328 | 0.020731429 | 0.046913279 |
| FFR | 0.19857747 | 0.236834931 | 0.838463598 | 0.40282954 | -0.268601951 | 0.66575689 | -0.268601951 | 0.665756887 |

**Figure 11: Federal Funds Rate vs. Gross Spread Line Fit Plot**

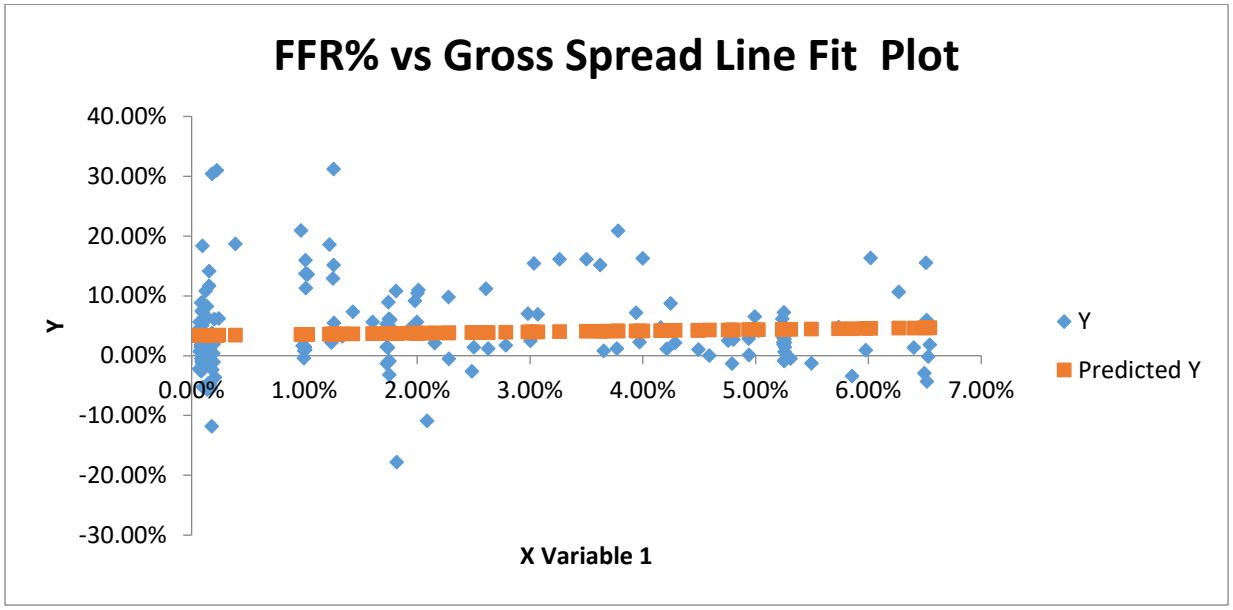
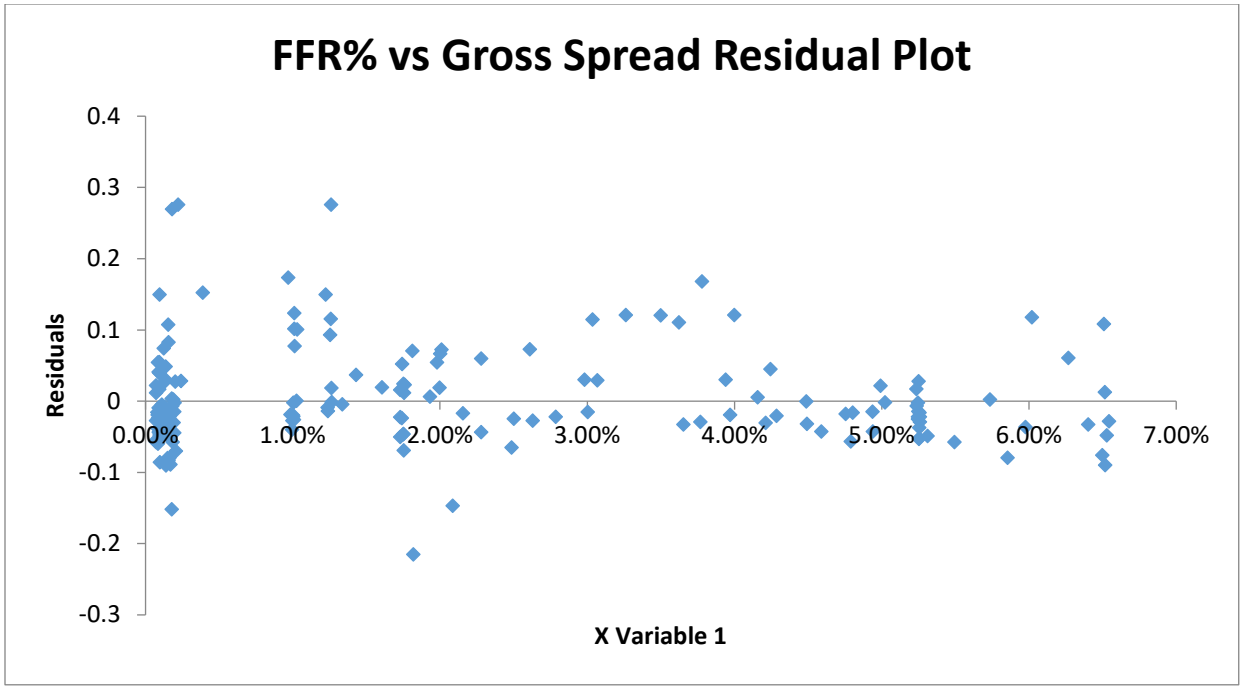


Figure 12: Federal Funds Rate vs. Gross Spread Residual Plot




**Δ S&P 500 P/E Ratio and Gross Spread Regression**

The final explanatory variable tested is the percentage change in the S&P 500's monthly P/E ratio, used as a proxy for market-wide valuation trends. Again, the correlation coefficient is a positive number, supporting the theorized relationship between the two variables, which associates rising asset valuations to widened gross spreads of M&A deals. In Figure 8, it is evident that there is a higher degree of clustering and variability of Gross Spreads at low Δ S&P P/E values, between 0%-20%, which is inconsistent with expectations. The few Δ S&P P/E values between 20%-40%, however, provide evidence that relatively higher gross spread values occur most often with spikes in valuation. With a P-value of .004, the null hypothesis is rejected, and the explanatory power of the x-variable on the y-variable is considered statistically significant.

**Table 6: Δ S&P P/E Ratio vs. Gross Spread Regression Output**

| *Regression Statistics* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Multiple R | 0.203096674 | | | | | | | |
| R Square | 0.041248259 | | | | | | | |
| Adjusted R Square | 0.036175498 | | | | | | | |
| Standard Error | 0.06686694 | | | | | | | |
| Observations | 191 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 1 | 0.03635667 | 0.03635667 | 8.13132388 | 0.00483456 | | | |
| Residual | 189 | 0.84505446 | 0.00447119 | | | | | |
| Total | 190 | 0.88141113 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | 0.037108788 | 0.00484074 | 7.66592767 | 9.0612E-13 | 0.02755996 | 0.046657615 | 0.027559962 | 0.046657615 |
| Δ S&P P/E Ratio | 0.157680353 | 0.05529641 | 2.85154763 | 0.00483456 | 0.04860292 | 0.266757783 | 0.048602922 | 0.266757783 |

**Figure 13: Δ S&P P/E Ratio vs. Gross Spread Line Fit Plot**

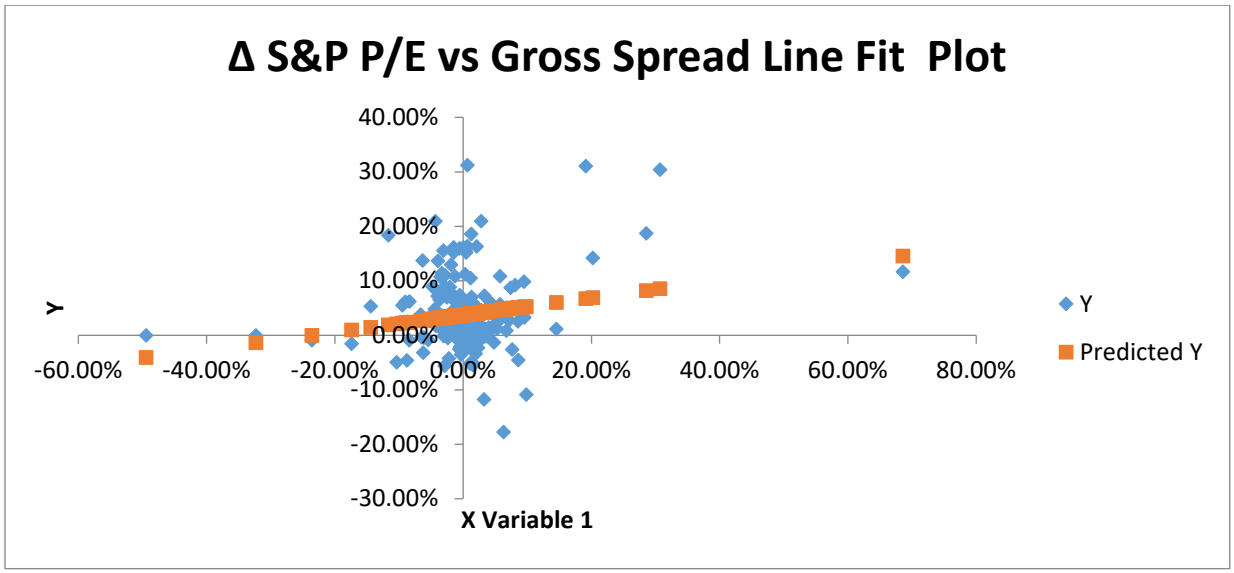
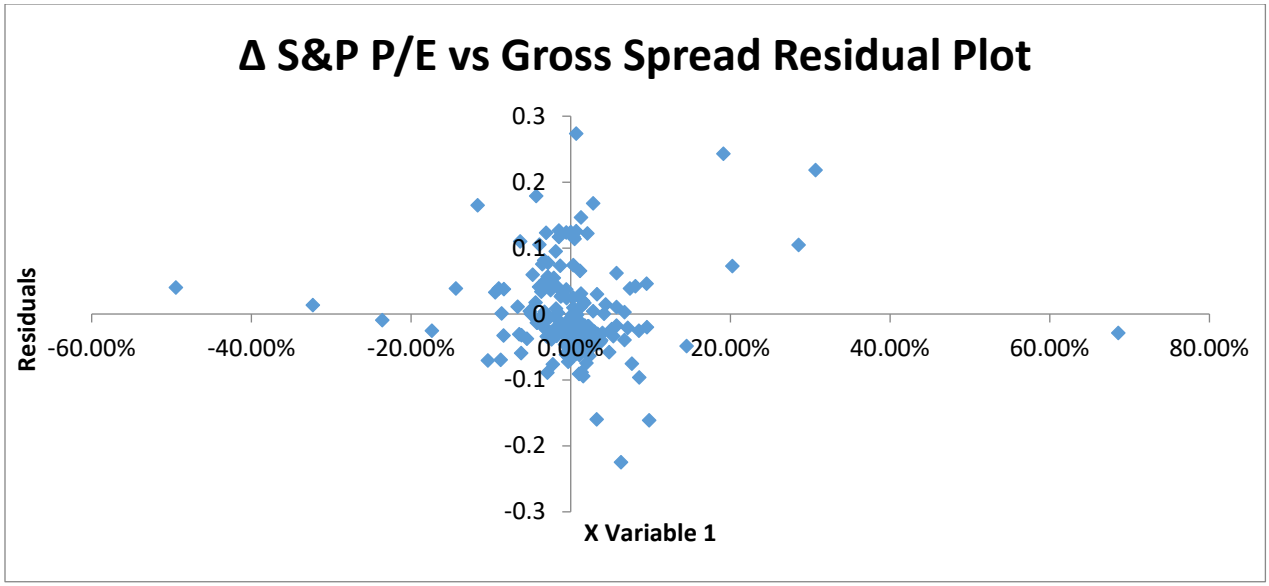


Figure 14: Δ S&P P/E vs. Gross Spread Residual Plot



## Chapter 6: Multivariable Regression Results and Analysis

Regressions testing the relationships between the statistically significant explanatory variables were run to observe their combined explanatory power over the dependent variable, Gross Spread. The same assumptions regarding the X-variable coefficients hold, and the null hypothesis will be rejected for any P-value < 0.10.

Because the Federal Funds Rate and the Deal Frequency are not statistically significant in their respective single-variable regressions against Gross Spread, these two variables are not included in the multivariate regression. With the remaining two explanatory variables, the average monthly price of the VIX and Δ S&P 500 P/E Ratio are tested against M&A average Gross Spread data.

## Multicollinearity of Explanatory Variables

**Figure 15: Time Series of VIX and S&P P/E Ratios**

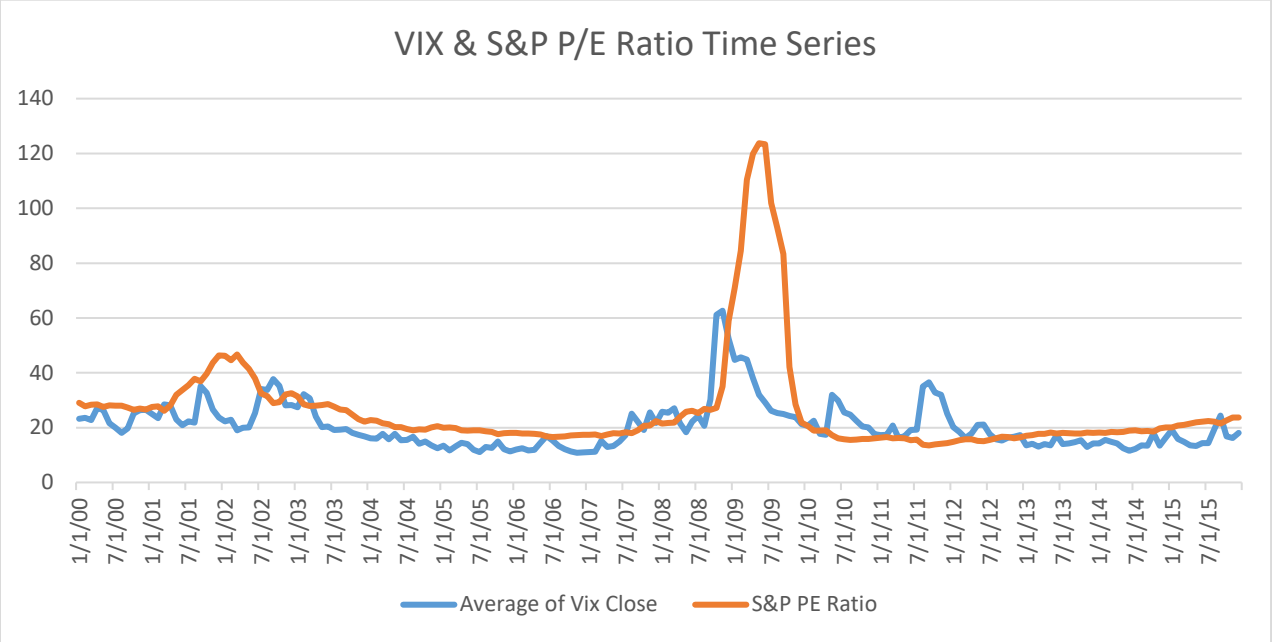



Figure 9 plots the monthly VIX and S&P 500 P/E Ratios over the 2000-2015 time-frame, and the synchronized movements of the two measurements is apparent. This can be interpreted as multicollinearity between the two variables, which will not reduce the predictive power of the regression but will be assumed to affect the multivariate outputs for the individual x-variables.

# Multivariate Regression Output

**Table 7: Multivariable Regression Output**

| *Regression Statistics* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Multiple R | 0.35804537 | | | | | | | |
| R Square | 0.128196487 | | | | | | | |
| Adjusted R Square | 0.118921982 | | | | | | | |
| Standard Error | 0.0639322 | | | | | | | |
| Observations | 191 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | *df* | *SS* | *MS* | *F* | *Significance F* | | | |
| Regression | 2 | 0.112993811 | 0.056496906 | 13.82246071 | 2.50813E-06 | | | |
| Residual | 188 | 0.768417323 | 0.004087326 | | | | | |
| Total | 190 | 0.881411134 | | | | | | |
| | | | | | | | | |
| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
| Intercept | -0.013098625 | 0.012484521 | -1.049189226 | 0.295437918 | -0.037726375 | 0.01152912 | -0.0377264 | 0.01152912 |
| VIX | 0.002438134 | 0.000563064 | 4.330120538 | 2.4209E-05 | 0.001327399 | 0.00354887 | 0.0013274 | 0.00354887 |
| Δ S&P P/E Ratio | 0.091553005 | 0.055030914 | 1.663664998 | 0.097845403 | -0.017004426 | 0.20011044 | -0.0170044 | 0.20011044 |

**Figure 16: Multivariate VIX vs. Gross Spread Line Fit Plot**

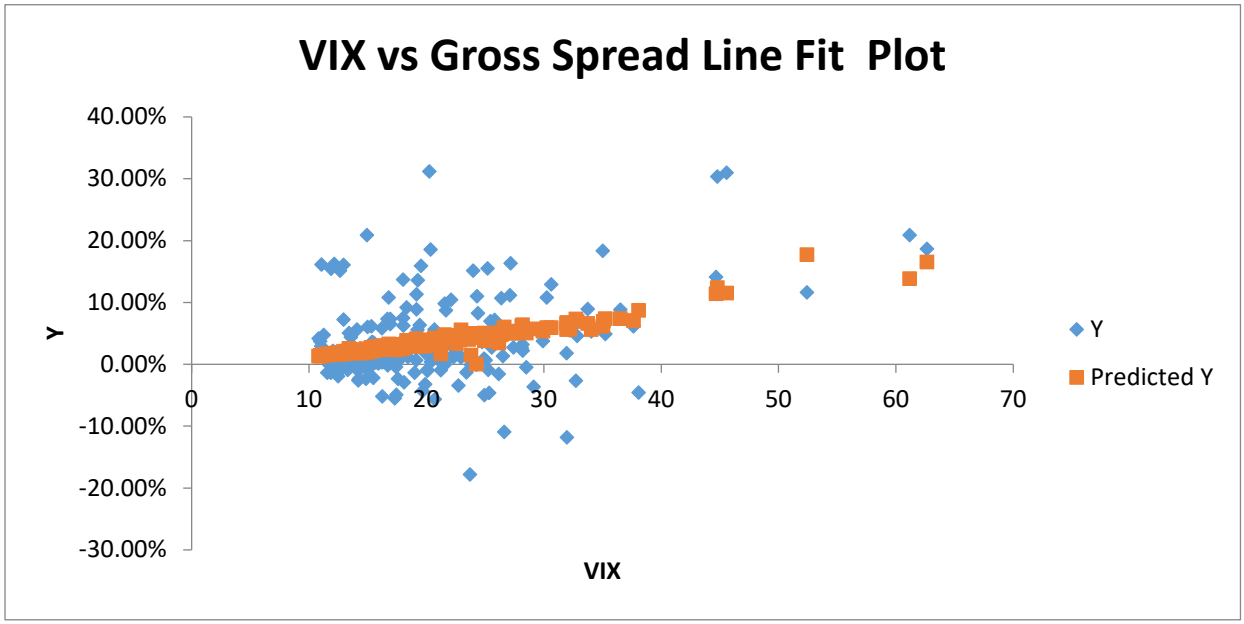
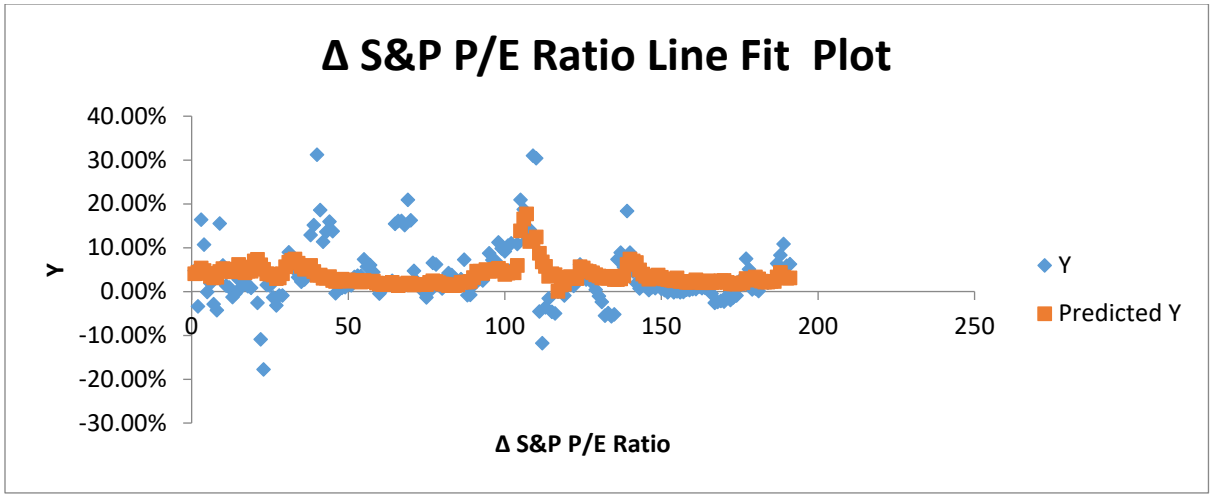


Figure 17: Multivariate Δ S&P P/E Ratio vs. Gross Spread Line Fit Plot




The combined explanatory power of the selected x-variables provides an R-square value of .128, which is stronger than any of the single-variable regressions run. Once more, Table 7 reports positive correlation coefficients for variables, supporting that as the VIX and Δ S&P P/E values increase, and liquidity will be suppressed, driving wider spreads between bid-ask prices. Table 7 also reveals that both the VIX and Δ S&P P/E have P-values below the 0.10 cutoff, deeming both statistically significant.

## Implications

The multivariate regression output in Table 7 provides evidence that there is a statistically significant, positive relationship between Gross Spread (%) of M&A activities and the proxies for volatility and market valuation. These results suggest that the VIX and Δ S&P P/E values, in their relationships to liquidity as discussed in Chapter 4, hold the most explanatory power over M&A arbitrage gross spread convergence and widening.

# Chapter 7: Conclusions

From the regressions results presented in Chapter 6, several conclusions can be made in response to the research question: what forces of liquidity have the most explanatory power over M&A deal gross spread behavior? From the four selected explanatory variables to be measured against gross spread, the monthly price of the VIX and the monthly percentage change in the S&P 500's P/E ratio are the only variables that showed statistically significant co-movement with the y-variable. The monthly Federal Funds Rate and M&A deal frequency are not used in the multivariable regression to avoid overfitting the curve.

From the multivariable regression, using the two statistically significant explanatory variables, a statistically significant relationship between the variables is confirmed. From this, it can be concluded that gross spreads of M&A deals move with market-wide risk expectations and valuation trends. According to the regressive output, as perceived risk and valuation increase, gross spread values will increase. Without assuming causality, these relationships connect liquidity measures to the ability of arbitrageurs to keep prices close to fundamental values, at a minimum.

## Shortcomings

Finally, the shortcomings of this experiment are recognized for the benefit of any potential recreations of this study. To begin, there is always room for the sample size of data to expand. For this paper, a total of 339 M&A deals are used to calculate an average gross spread over time. For future studies of liquidity effects on M&A merger spreads, a greater sample size would have

benefited the accuracy of the results. In addition to a larger sample size, a sample including failed deals in addition to successfully completed deals would also be helpful in order to gauge the risk of failure for this time period.

Secondly, the regression output could provide more information had the interactions between the explanatory variables been measured. Multicollinearity among x-variable coefficients is only acknowledged and superficially observed among the explanatory variables VIX and the S&P 500's P/E in this paper.

Thirdly, the application of these results to French and Fama's industry classification system would have allowed the comparison of the results to industry-based theories of M&A activity. From this, explanatory variables related to particular industries could be chosen for regression analysis, providing insights of industry-specific insights.

Lastly, a useful continuation of this study may include regression analysis that observes the explanatory variables in time periods outside of the Financial Crisis, especially in the case of the VIX variable. This would ensure that the hypothesized relationships hold true even outside of an economic shock.

The results from this study offer insights into the relationship between market liquidity and M&A arbitrage gross spreads, however, additional research is necessary to ensure that the relationship between these variables holds outside of the constraints of this study. A larger

selection of explanatory variables, combined with a larger and more varied deal sample, should provide more comprehensive conclusions.

Appendix A: Data Sources

Merger and Acquisition Data in Thompson Reuters: The raw data set was pulled using the following steps: *Thompson 1* > *Screening and Analysis* > *Deals and League Tables* > *M&A* > *Advanced Search*

| Request | Operator | Description |
|---|---|---|
| Database | Include | All Mergers & Acquisitions |
| Date Announced | Between | 01/01/2000 to 12/31/2015 |
| Target Public Status (Code) | Include | Public |
| Acquiror Nation (Code) | Include | United States of America |
| Target Nation (Code) | Include | United States of America |
| Custom Report | | MA 2 output... |

| FILTERS |
|---|
| % Sought = 100% |
| Status = Completed |
| Merger Types = Cash, Stock, Cash & Stock |

Target Stock Trading Dates, Prices and Dividend Data in FactSet: All FactSet values were pulled using the FactSet Excel add-in. Each field was returned using the following formulas:

- Date = *P_Date* for dates between the announcement and closing dates
- Price = *FG_Price*
- Dividends = *P_DIVS_PD_F*

S&P 500 Monthly P/E Ratio Data: S&P P/E ratios were copy and pasted from the table, by month, from January, 2000 to December 2015.

http://www.multpl.com/table?f=m

VIX Monthly Price Data: Monthly VIX closing price values were copy and pasted from the table found in the link below. The link reflects the format of these prices, which were pulled from January 2000 to December 2015.

https://finance.yahoo.com/quote/%5EVIX/history?period1=946702800andperiod2=1451538000andinterval=1moandfilter=historyandfrequency=1mo

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# Academic Vita of Grace Hill

Grp5097@psu.edu

THESIS TITLE: An Analysis of Merger Arbitrage Spreads
THESIS ADVISOR: Dr. David Haushalter

EDUCATION:

**The Pennsylvania State University** — University Park, PA
*Schreyer Honors College, Smeal College of Business* — Class of 2018
*Major:* Bachelor of Science: Finance
*Minor*: International Business
Honors/Awards: The Robert W. Koehler Award recipient; Dean's List; Presidential Freshman Award

**University of Amsterdam** — Amsterdam, Netherlands
*Program:* Study Amsterdam — January 2017 – June 2017

**International Studies Institute** — Florence, Italy
*Program:* The World of Business and Italian Culture — May 2015 – July 2015

EXPERIENCE:

**Siemens Medical Solutions** — Malvern, PA
*Financial Leadership Development Intern* — May – August 2016, June – August 2017

- Hired to work on special projects for the Accounting and Solutions Implementation departments
- Prepared and presented reports analyzing union labor performance and costs for the director of the NY Metro region

**Abundance Wealth Counselors** — State College, PA
*Investment Department Intern* — August 2015 – February 2017

- Maintained appropriate cash levels based on unique client needs
- Prepared and distributed a report examining investment performance and market strategy to inform employees and clients of market conditions

LEADERSHIP:

**Phi Chi Theta Business Fraternity** — University Park, PA
*PCT Investment Fund Founder and President* — December 2014 – May 2017

- Managed a hypothetical moderate-risk portfolio using a variety of investment strategies
- Generated a 9-month lesson plan for the structure of the organization

**Smeal Student Mentors** — University Park, PA
*Student Mentor and Writer* — February 2015 – December 2017

- Advise incoming Smeal freshmen on academic planning according to their intended major and Smeal class requirements
- Serve as a reference point for any academic questions or concerns from underclassmen
- Compose articles for the organization's monthly publication *The Monthly Mentor*

**Undergraduate Economics Teaching Assistant** — University Park, PA
*Head Teaching Assistant* — January 2015 – May 2015

- Reviewed and scored Econ 296 assignments to support professor